# Online Appendix to: What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality

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## Pollution Decompositions

### *A1. Oaxaca-Blinder Decomposition of Racial Pollution Gaps*

Assume that for an individual $i$ in group $g \in \{b, w\}$ pollution exposure $P_{gi}$ can be written as a linear function of observed characteristics ($X_{gi}$) and an error term $\mu_{gi}$

$$P_{gi} = \beta_g X_{gi} + \mu_{gi} \tag{A1}$$

where $\beta_g$ are defined so that $E[\mu_{gi} \mid X_{gi}] = 0$. The difference in expected pollution exposure for Blacks and Whites can be written as:

$$P_b - P_w = (X_b - X_w)\,\beta_b + (\beta_b - \beta_w)\,X_w \tag{A2}$$

where $P_g$ and $X_g$ represent mean pollution and mean characteristics for all individuals in group $g$. The first term on the right-hand side of equation (2) is the part of the gap explained by differences in the average observable characteristics of the two groups; namely, how large would the observed pollution gap be if we gave Blacks the same mean characteristics as Whites? The second term is the part of the mean difference in pollution exposure that is not explained by differences in characteristics; instead it reflect differences in the "returns" to the observable characteristics (that is, the differences in slopes between groups, $\beta_b - \beta_w$, for each observed characteristic).

The results of this initial decomposition are shown in Appendix Table B4 for the two end points of our sample, 2000 and 2015. The first row shows the predicted difference in pollution exposure obtained from left hand side of equation (A2): The gap is -1.616 $\mu$g/m$^3$ in 2000, falling to -0.544 $\mu$g/m$^3$ by 2015. The first panel of Table B4 ("Explained") shows that very little of the racial gap in predicted pollution exposure can be explained by an individual's observable characteristics. While African American households have mean household income more than $15,000 less than non-Hispanic Whites (see Appendix Table B2), these differences in income explain almost none of the observed differences in pollution exposure. In fact, almost none of the observed individual or household characteristics are able to explain any portion of the observed difference in pollution exposure. Only 4.8 percent of the gap (-0.078/-1.616) is explained by differences in income, age, schooling, children, gender, and/or homeownership. In 2015, differences in these characteristics between Blacks and Whites are able to explain only 8 percent (-0.044/-0.544) of the gap in pollution exposure between Black and Whites. Differences in mean homeownership rates between racial groups are able to explain about 4-6 percent of the gap.[19] Hence, differential racial exposure to pollution cannot be explained simply by the fact that African Americans are more disadvantaged in terms of measured characteristics on average than non-Hispanic Whites.

The second panel of Table B4 ("Unexplained") shows that the bulk of the racial gap in pollution exposure instead reflects racial differences in the "returns" to observed characteristics and/or differences in unmeasured characteristics. In particular, differences in the coefficients on age and education explain a significant portion of the gap in both 2000 and 2015.

### *A2. Decompositions Using Recentered Influence Functions (RIF)*

While the previous section explored differences in mean outcomes between Blacks and Whites, it is also possible to decompose other parts of the pollution distribution (e.g., the 10th or 90th percentiles of the White and Black pollution distributions). Are observable characteristics able to explain more of the difference in outcomes at the 90th percentiles? What about the 10th percentiles? Recent advances in quantile regression allow us to decompose differences in quantiles of the unconditional pollution distribution using recentered influence functions (RIF) (Firpo, Fortin and Lemieux, 2009). The basic idea is to transform the problem by considering a covariate's influence on population shares rather than quantiles. By estimating how a covariate (e.g., income) affects the share of the population below various pollution thresholds, we can identify the marginal effect of income on the cumulative distribution function (CDF) of pollution. We can then invert the impact of income on the CDF of pollution to estimate the impact on a pollution quantile. The RIF regression approach proposed by Firpo, Fortin and Lemieux (2009) performs this inversion using a local linear approximation to the counterfactual CDF, rescaling the marginal effect of each covariate on the share above a pollution cutoff by the probability density of pollution at that cutoff.

In practice, RIF regression requires first transforming the outcome variable, PM2.5 pollution, using a recentered influence function before projecting this

[19] We have experimented with a range of more flexible functional forms for all the control variables, and the qualitative results are nearly identical when including higher order polynomials and/or more flexible dummy variable transformations of the observed continuous variables.

transformation on the explanatory variables of interest. RIF-regression methods provide a simple way of performing decompositions for any distributional statistic for which an "influence function" can be computed.

Firpo, Fortin and Lemieux (2009) consider the following model of pollution P:

$$P = h(X, \epsilon)$$

where $X$ represents the set of independent, explanatory variables and $\epsilon$ is the scalar unobserved error term. The unconditional partial effect is defined as the shift in the distribution of a variable $X$ on the distributional statistic $v(F_P)$, which can be expressed as

$$\int \frac{dE[\mathrm{RIF}(P, v)|X = x]}{dx} dF(x)$$

where $\mathrm{RIF}(P, v)$ is the recentered influence function. When the distributional statistic $v$ is the $\tau$th quantile function $q_t = \inf_q \{q : F_P(q) \geq \tau\}$ the $\mathrm{RIF}(P, q_\tau)$ can be represented as:

$$\mathrm{RIF}\,(P, q_\tau) = q_\tau + \frac{\tau - 1\,\{p \leq q_\tau\}}{f_P\,(q_\tau)},$$

where $f_P(q_\tau)$ is the density function of pollution $P$ evaluated at quantile $q_\tau$.

The relevant property of a recentered influence function is that its expectation equals the distributional statistic of interest. For quantile $\tau$ denoted $Q_\tau$, the quantile RIF is given by $\mathrm{RIF}\,(p, Q_\tau) = Q_\tau + \frac{\tau - \mathbf{1}(p<Q_\tau)}{f_p(Q_\tau)}$ and taking expectations verifies $E\,[RIF(p, Q_\tau)] = Q_\tau$. Since the mean of the RIF is equal to the quantile, we can use the law of iterated expectations to decompose each unconditional quantile, as Oaxaca (1973) and Blinder (1973) do when they decompose the mean.

Firpo, Fortin and Lemieux (2009) show that a regression of the RIF on covariates yields the approximate effect of the covariates on the distributional statistic of interest (applied to the unconditional distribution). As we show in the text, this feature of RIF regressions provides a natural bridge to exploring how treatment effects (e.g., the effects of the CAA PM2.5 regulations on county-year pollution levels) map into the unconditional distribution of pollution.

Appendix Table B5 shows the results of decompositions of the 10th, 50th, and 90th percentiles of the pollution distributions for non-Hispanic Whites and African Americans using re-centered influence functions. The first three columns show the estimates for 2000, while the last three columns show the estimates for 2015. Both sets of estimates indicate larger gaps at the 10th percentile than at the 90th percentile. These patterns of quantile differences can largely be explained by recognizing that both non-Hispanic Whites and African American live in large cities with high levels of air pollution (i.e. the 90th percentiles of their respective pollution distributions are somewhat similar); whereas rural locations, that also tend to be the least polluted parts of the United States, are disproportionately White, leading to larger gaps in the 10th percentiles of the respective race-specific pollution distributions. As in the Oaxaca-Blinder decompositions, these breakdowns indicate that relatively little of the predicted differences in exposure can be explained by differences in individual and household level characteristics. By 2015, the racial gap in the 90th percentile of exposure has narrowed significantly, and, for the first time, most of the gap can be accounted for by differences in observable characteristics. For the most part, however, the quantile decompositions present a pattern similar to the original mean decompositions; Black-White differences in individual or household-level characteristics explain very little of the Black-White difference in PM2.5 pollution exposure, especially in earlier years.

### *A3. People versus Places: Decomposing the Role of Population Shifts in Changing the Pollution Gap*

We consider an alternative mobility decomposition in order the further explore the role of reallocation of population shares within racial groups over time. We consider pollution exposure ($\Omega$) as the population share (denoted by $s_{it}$) weighted average of tract $i$ level pollution in year $t$ $\omega_{it}$. We rely on the following definition of nationwide pollution exposure in year $t$ $\Omega_t = \sum_i s_{it}\omega_{it}$, which corresponds to the share weighted average of census tract pollution exposure over all $i$ tracts. This differs from the unweighted average of census tract pollution exposure in a given year $\overline{\omega_t} = \frac{1}{N_t}\sum_i \omega_{it}$.

We decompose this nationwide pollution term into unweighted tract-level pollution and the covariance between pollution and tract-level population shares. The same decomposition can be applied by race group $\phi$, which can inform us whether the observed pollution changes are driven mostly by improvements in average census tracts versus shifts in race-specific population shares across census tracts over time. Denote the population share of each race group as $s(\phi)_t = \sum_{i\in\phi} s_{it}$. Likewise, denote race-specific pollution is $\Omega_t(\phi)$, while the average tract-level pollution within a race group is $\bar{\omega}_t(\phi)$ Then we can write nationwide pollution exposure as a weighted average of the race-specific components

$$\Omega_t = \sum_{\phi\in b,w} s_t(\phi)\left(\bar{\omega}_t(\phi) + \sum_{i\in\phi}\left(\omega_{it} - \bar{\omega}_t(\phi)\right)\left(s_{it}(\phi) - \bar{s}_t(\phi)\right)\right). \tag{A3}$$

$$= \sum_{\phi\in b,w} s_t(\phi)\left(\bar{\omega}_t(\phi) + \Gamma_t(\phi)\right) \tag{A4}$$

where $\Gamma_t(\phi)$ reflects the covariance between population shares and pollution levels for a respective race group. If African Americans are more concentrated in census tracts with high pollution levels, this term will be positive for African Americans.

This equation allows us to explain changes in nationwide pollution, through (i) changes in the average pollution of Black and White census tracts ($\bar{\omega}_t(\phi)$), and (ii) changes in the covariance between population shares and pollution, separately for both Blacks and Whites ($\Gamma_t(\phi)$).

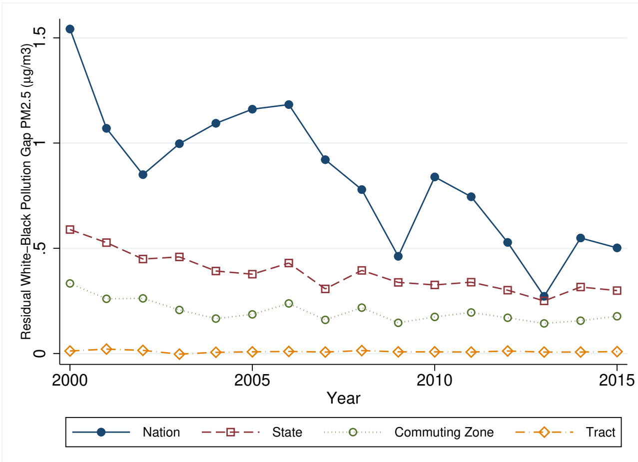
We perform this decomposition year by year to better understand the dynamics of this covariance term; if the covariance is falling over time, this would suggest that African Americans were becoming less concentrated in neighborhoods with the worst air quality. If the covariance term were relatively constant over time, the observed improvement in air quality for African Americans is primarily the result of the average African American census tract getting cleaner.

Appendix Figure B3 shows the results of implementing the decomposition in equation (4) year-by-year, separately for non-Hispanic Whites and African Americans. Appendix Table B7 similarly decomposes the 2000-2015 difference in PM2.5 exposure. Figure B3a shows that there is little change in the covariance between air pollution levels and share African American in a Census tract. However, over time, the negative relationship between pollution and non-Hispanic White population shares weakens.

Figure B3b shows that for African Americans, there is virtually a one to one relationship between average individual exposure and the unweighted mean census tract pollution level, consistent with the flat trend in the covariances in Figure B3a. Hence, among African Americans, virtually all of the reduction in pollution exposure can be accounted for by the average African American tract cleaning up, rather than by relocation of African Americans to relatively cleaner tracts. Formally, Column (2) of Table B7 suggests 93% of the 2000-2015 improvement in air quality for African Americans can be explained by changes in the average African American tract. The remaining seven percent can be explained by a weakening of the covariance between African American population shares and pollution exposure. Figure B3c shows that the average White pollution exposure is slightly lower than average tract-level exposure, indicating that Whites live in cleaner tracts. However, this gap narrows over time, consistent with the trend in covariances shown in Figure B3a. Overall then, this decomposition indicates that a small part of the gap between African Americans and non-Hispanic Whites can be accounted for by Whites becoming less concentrated in the relatively cleanest neighborhoods, but that most of the relative air quality improvement for African Americans reflects clean ups within tracts rather than relative shifts in Black-White population shares to cleaner or dirtier tracts.

# Appendix Tables and Figures

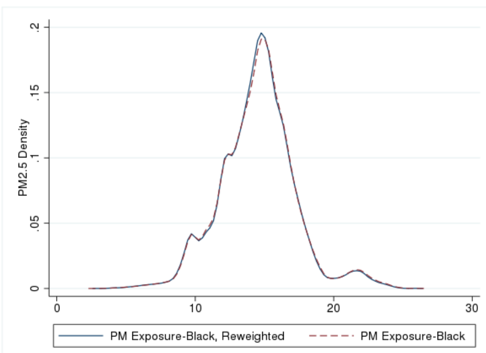
Figure B1. : Trends in Pollution Exposure Gaps by Geography



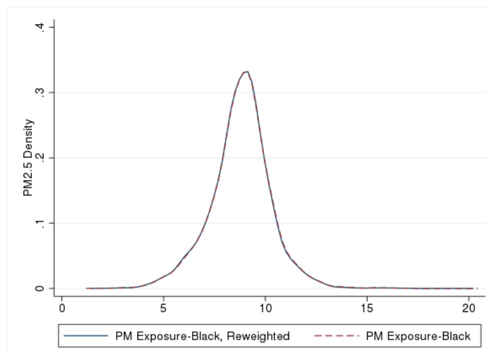

Notes: This figure plots the average, within geography difference in PM2.5 exposure between African-Americans and non-Hispanic White individuals at different levels of geographic resolution. For example, the line corresponding to "Commuting Zone" plots the average within-Commuting Zone difference in PM2.5 exposure between African Americans and non-Hispanic Whites in our sample. In practice, these conditional mean differences are constructed by estimating a version of equation (1), regressing individual PM2.5 exposure on an indicator for whether that individual is African American and a set of fixed effects corresponding to the geography of interest. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Figure B2. : Actual versus Counterfactual African American Pollution Distribution: PM2.5

(a) Reweighted vs. Actual PM2.5 Density
African Americans, 2000



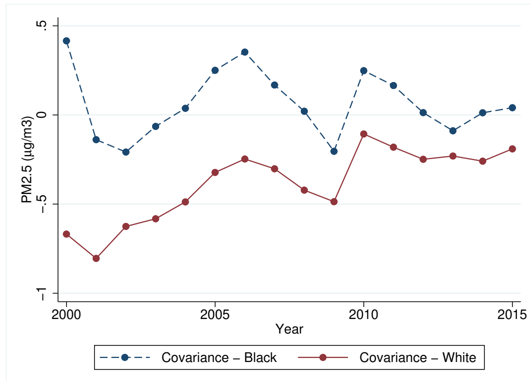

(b) Reweighted vs. Actual PM2.5 Density
African Americans, 2015



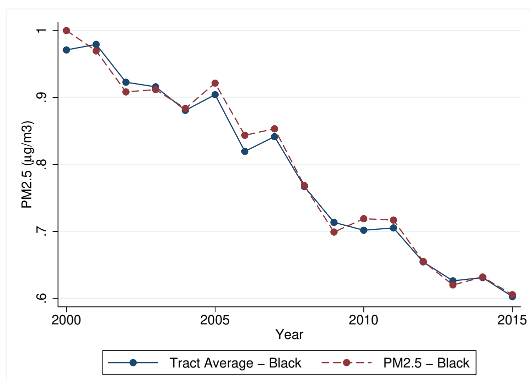

NOTES: These figures plot the actual versus counterfactual densities of pollution exposure for African Americans in 2000 and 2015. The counterfactual densities stem from an application of Dinardo, Fortin, Lemieux (1996), whereby we reweight the African American pollution distribution to reflect what the distribution would have looked like if they had the same individual characteristics as non-Hispanic Whites in our sample. See text for details. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Figure B3. : Individual vs. Tract-Level Exposure and Covariance Between Race Share and Air Quality

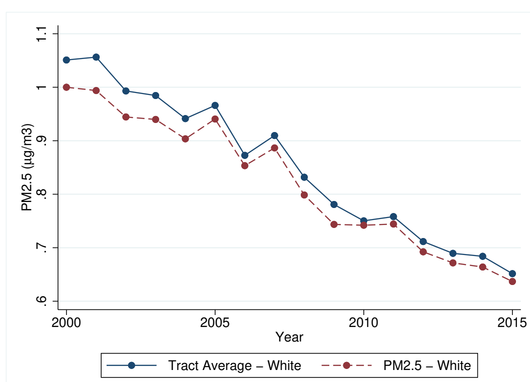
(a) Tract PM2.5 and Population Share Covariances




(b) Individual and Tract Average PM2.5 Exposure: African Americans

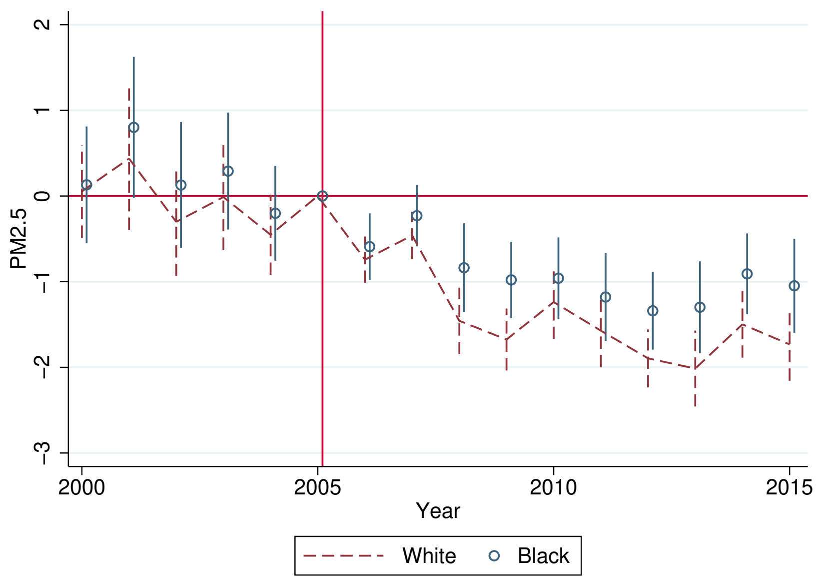



(c) Individual and Tract Average PM2.5 Exposure: non-Hispanic White



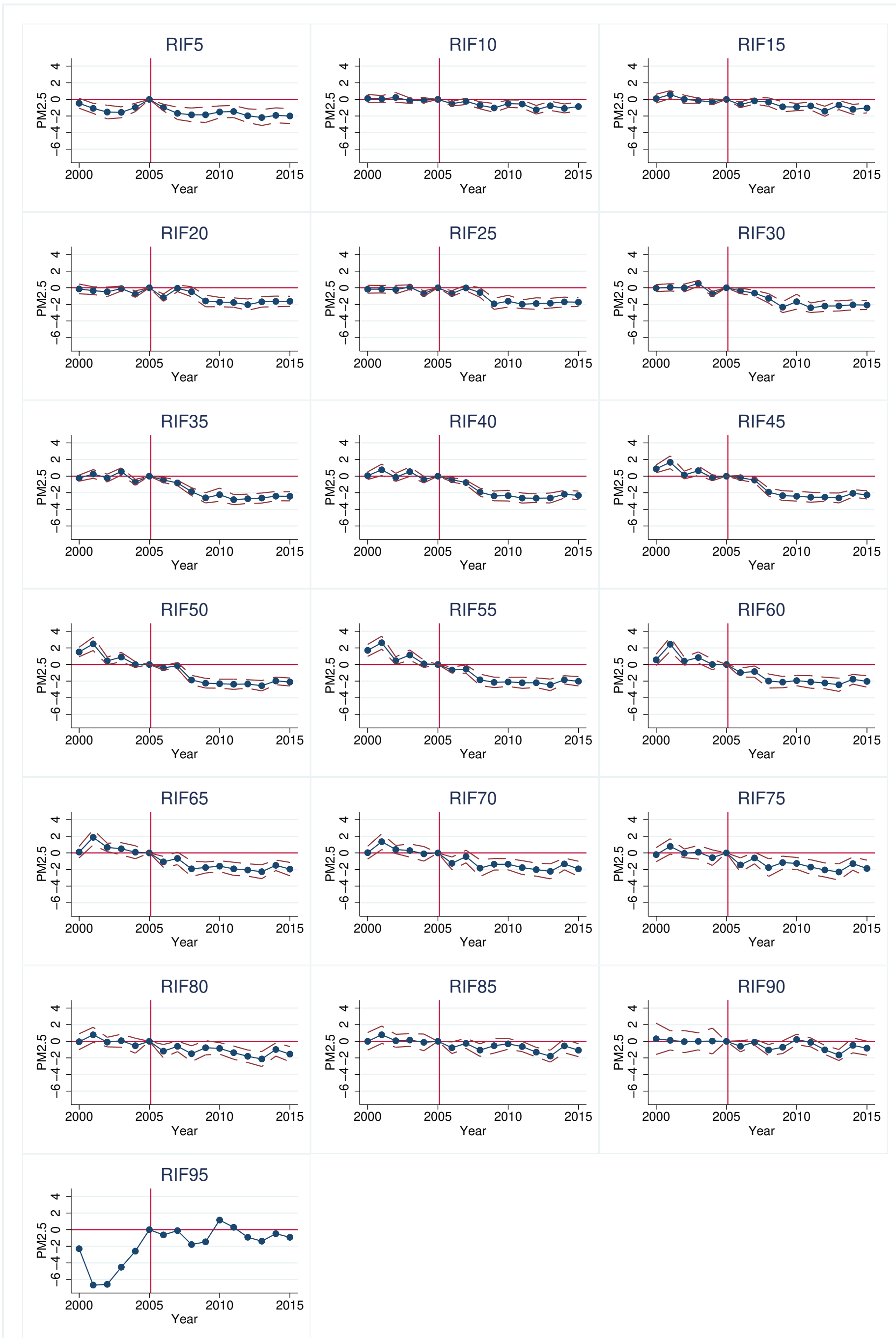

Notes: These figures present results from decomposing average PM2.5 exposure into the unweighted average Census tract exposure for each race group and the assortative relationship between race-specific population shares and pollution levels. Figure (a) presents the year-by-year covariance between race-specific population shares and pollution levels, separately by race. Figure (b) plots the population-weighted trend in PM2.5 exposure for African Americans (dashed line) and the trend in unweighted Census tract exposure for African Americans (solid line). Figure (c) replicates Figure (b) for Non-Hispanic Whites. See text for details. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Figure B4. : The Effect of the PM2.5 NAAQS on Newly Regulated Commuting Zones, By Race



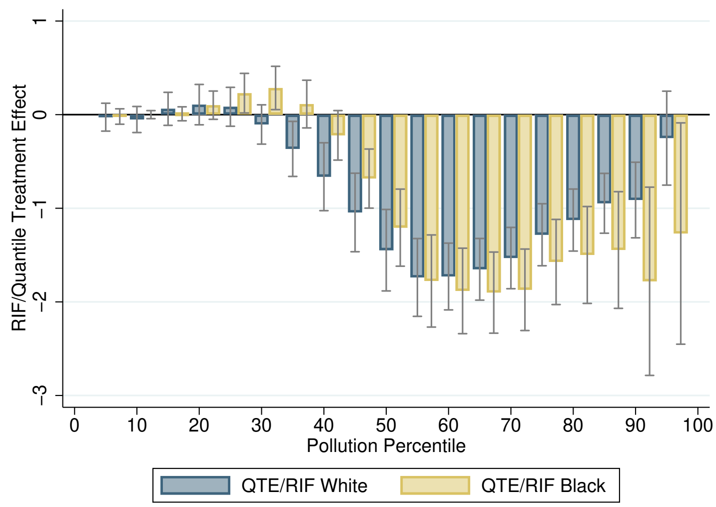

Notes: This figure plots the event-time coefficient estimates from a version of equation (2), where the dependent variable consists of PM2.5 exposure ($\mu g/m^3$) for a given individual-year. This figure estimates equation (2) separately by race. The regression model controls for county and year fixed effects. The red dashed lines correspond to estimates for non-Hispanic White individuals. The hollow circles correspond to estimates for African Americans. The vertical lines represent 95% confidence intervals for the respective point estimates. Regressions are weighted by Census survey weights and errors are clustered by commuting zone. Source: Decennial Census, American Community Survey, EPA NAAQS Greenbook, Di et al. (2016).

Figure B5. : The Effect of the PM2.5 NAAQS on Newly Regulated Commuting Zones, By Quantile




Notes: This figure plots the event-time coefficient estimates from a version of equation (2), where the dependent variable consists of the corresponding RIF-Quantile transformation of PM2.5 exposure ($\mu$g/m$^3$) for a given individual-year. This figure estimates equation (2) separately by RIF-Quantile, as indicated in the subfigure headings. The regression model controls for county and year fixed effects. The red dashed lines correspond to estimates of the 95% confidence intervals for the respective point estimates. Confidence intervals on the last figure have been suppressed due to noisy estimates and to maintain a common y-axis. Regressions are weighted by Census survey weights and errors are clustered by commuting zone. Source: Decennial Census, American Community Survey, EPA NAAQS Greenbook, Di et al. (2016).

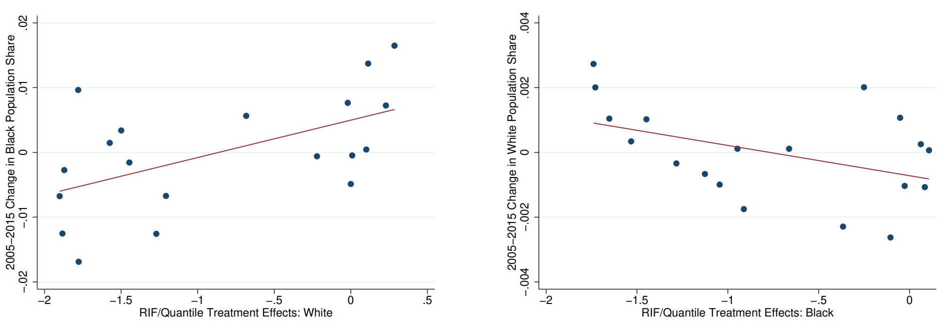
Figure B6. : Race-Specific RIF-Quantile Treatment Effects of the 2005 CAA PM2.5 NAAQS Implementation




Notes: This figure reproduces Figure 8, including confidence intervals for the regression coefficients. The figure plots the regression coefficient $\hat{\beta}$ from 38 separate versions of equation (3), 19 regressions for each race, where the dependent variable consists of the RIF-Quantile transformation of the respective PM2.5 vigintile (indicated by the x-axis). The regression model controls for county fixed effects and state-by-year fixed effects. The solid gray lines represent 95% confidence intervals. Regressions are weighted by Census survey weights and errors are clustered by commuting zone. Source: Decennial Census, American Community Survey, EPA NAAQS Greenbook, Di et al. (2016).

Figure B7. : 2005-2015 Change in Population Plotted Against Quantile Treatment Effects

(a) African Americans (b) Non-Hispanic White




Notes: Figure B7a plots the within-quantile change in the Black population share between 2005 and 2015 against the RIF-quantile treatment effects for Blacks in the respective quantile (i.e. taken from Figure 10). Figure B7b repeats this exercise for non-Hispanic Whites. An observation corresponds to a particular quantile bin. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B1—: Spatial Determinants of 2000-2015 Changes in PM2.5 Exposure

| | (1) State Fixed Effects | (2) County Fixed Effects | (3) Tract Fixed Effects |
|---|---|---|---|
| | Panel A: PM2.5 Exposure 2000 | | |
| Fraction of Variation Explained | 0.568 | 0.877 | 0.983 |
| N | 14430000 | 14430000 | 14430000 |
| | Panel B: PM2.5 Exposure 2015 | | |
| Fraction of Variation Explained | 0.415 | 0.764 | 0.956 |
| N | 1524000 | 1524000 | 1524000 |
| | Panel C: PM2.5 Exposure 2000-2015 | | |
| Fraction of Variation Explained | 0.418 | 0.767 | 0.952 |
| N | 817000 | 817000 | 817000 |

Notes: This table explores the fraction of the variation in PM2.5 exposure that can be explained by different geographies, and correspondingly, how much within geography variation is left over. Panel A uses the 2000 Decennial Census and projects an individual's PM2.5 exposure on a set of geographic indicators (using population weights) to determine what fraction of this variation in individual exposure differences can be explained by state fixed effects, county fixed effects, or census tract fixed effects. Panel B does this for the 2015 American Community Survey respondents. Panel C uses the sample of individuals that appear in both the 2000 and 2015 Census and American Community Survey to calculate the 2000-2015 difference in PM2.5 exposure. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B2—: Summary Statistics by Race, Overall, and Sub-Periods

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Overall | | African-American | | Non-Hispanic White | | Mean Diff. | |
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | (5)-(3) | p-value |
| | | | Panel A: Individual Characteristics | | | | | |
| Age | 40.010 | 8.573 | 39.410 | 8.536 | 40.100 | 8.575 | 0.687 | (0.000) |
| Years of School | 13.650 | 2.650 | 13.130 | 2.405 | 13.720 | 2.674 | 0.587 | (0.000) |
| Sex (1=Female) | 0.514 | 0.500 | 0.549 | 0.498 | 0.509 | 0.500 | -0.041 | (0.000) |
| Homeowner | 0.703 | 0.457 | 0.486 | 0.500 | 0.733 | 0.443 | 0.247 | (0.000) |
| Number of Children | 1.070 | 1.213 | 1.039 | 1.267 | 1.074 | 1.206 | 0.035 | (0.000) |
| Income | 48130 | 51590 | 34300 | 34630 | 50070 | 53250 | 15760 | (0.000) |
| Bottom Income Quintile | 0.200 | 0.400 | 0.264 | 0.441 | 0.191 | 0.393 | -0.073 | (0.000) |
| Top Income Quintile | 0.200 | 0.400 | 0.106 | 0.307 | 0.213 | 0.410 | 0.108 | (0.000) |
| PM2.5 (Satellite, Block) | 10.770 | 2.980 | 11.460 | 2.748 | 10.680 | 2.999 | -0.780 | (0.000) |
| PM2.5 (Satellite, County) | 10.770 | 2.812 | 11.390 | 2.608 | 10.680 | 2.829 | -0.705 | (0.000) |
| PM2.5 (EPA Monitors, County) | 11.460 | 2.948 | 12.040 | 2.781 | 11.360 | 2.964 | -0.679 | (0.000) |
| | | | Panel B: Census Tract Characteristics in 2000 | | | | | |
| African American | 0.123 | 0.131 | 0.262 | 0.175 | 0.103 | 0.110 | -0.158 | (0.000) |
| Public Assistance Income | 34.04 | 39.98 | 34.35 | 40.89 | 33.99 | 39.85 | -0.352 | (0.902) |
| Income | 48130 | 12920 | 47660 | 12780 | 48200 | 12930 | 540 | (0.392) |
| Years of Schooling | 13.640 | 0.708 | 13.680 | 0.683 | 13.640 | 0.712 | -0.035 | (0.276) |
| % Worked Last Year | 0.834 | 0.047 | 0.828 | 0.046 | 0.835 | 0.047 | 0.007 | (0.012) |
| Housing Value | 292500 | 183000 | 292200 | 178900 | 292500 | 183500 | 299 | (0.980) |
| Housing Rent | 1096 | 317 | 1116 | 294 | 1094 | 320 | -22.220 | (0.203) |
| % Home Owners | 0.703 | 0.111 | 0.657 | 0.120 | 0.709 | 0.108 | 0.053 | (0.000) |
| % Single Family Residence | 0.831 | 0.051 | 0.822 | 0.049 | 0.833 | 0.051 | 0.011 | (0.000) |
| % in Urban County | 0.992 | 0.089 | 0.997 | 0.057 | 0.991 | 0.092 | -0.005 | (0.000) |
| % Manufacturing Emp. | 0.133 | 0.095 | 0.115 | 0.086 | 0.136 | 0.096 | 0.022 | (0.000) |
| | | | Panel C: County-Level Characteristics in 2000 | | | | | |
| African American | 0.129 | 0.232 | 0.556 | 0.320 | 0.069 | 0.134 | -0.487 | (0.000) |
| Welfare Income | 30.50 | 135.80 | 51.71 | 205.90 | 27.53 | 122.60 | -24.180 | (0.000) |
| Years of School | 13.590 | 1.409 | 13.150 | 1.305 | 13.650 | 1.412 | 0.496 | (0.000) |
| Single Family Residence | 0.824 | 0.163 | 0.792 | 0.186 | 0.829 | 0.159 | 0.037 | (0.000) |
| Teen Pregnancy | -0.042 | 0.061 | -0.063 | 0.074 | -0.039 | 0.058 | 0.024 | (0.000) |
| Home Ownership | 0.720 | 0.204 | 0.603 | 0.236 | 0.737 | 0.194 | 0.134 | (0.000) |

Notes: This table presents summary statistics for individual and neighborhood characteristics for our main analysis sample. Source: 2000 Decennial Census, American Community Survey 2001-2015, and Di et al. (2016).

Table B3—: Relationship between Individual/Household Characteristics and PM2.5 Exposure

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Panel A: 2000 Decennial Census | | | | | |
| | Full Sample | | non-Hispanic White | | African American | |
| | Linear | Flexible | Linear | Flexible | Linear | Flexible |
| Fraction of Exposure Explained | 0.005 | 0.008 | 0.003 | 0.007 | 0.003 | 0.004 |
| Observations | 10640000 | 10640000 | 9656000 | 9656000 | 980000 | 980000 |
| | Panel B: 2015 American Community Survey | | | | | |
| | Full Sample | | non-Hispanic White | | African American | |
| | Linear | Flexible | Linear | Flexible | Linear | Flexible |
| Fraction of Exposure Explained | 0.004 | 0.005 | 0.003 | 0.005 | 0.003 | 0.003 |
| Observations | 1152000 | 1152000 | 1048000 | 1048000 | 104000 | 104000 |

Notes: This table presents the adjusted R-squared from 12 separate regressions, 6 per panel. The "linear" specification regresses individual PM2.5 exposure on a linear set of controls including: log income, age, years of schooling, number of children, gender, and homeownership status. The "flexible" specification replaces log income with five income quintile dummy variables, a quadratic schooling term, and a quadratic age term. Panel A does this for the year 2000, and Panel B repeats this exercise in 2015. Regressions are weighted using Census survey weights. See text for details. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B4—: Decomposition of Mean Differences in Pollution Exposure into Components Explained by Differences in Individual Characteristics and due to Differences in “Returns” to Characteristics

| | (1) Year 2000 | (2) Year 2015 |
|---|---|---|
| Predicted difference | -1.616 | -0.544 |
| Panel A: Explained Gap | | |
| Income | -0.001 | 0.000 |
| Age | -0.009 | -0.002 |
| Schooling | -0.011 | -0.010 |
| Kids | 0.003 | 0.001 |
| Gender | 0.000 | 0.000 |
| Homeowner | -0.061 | -0.033 |
| Total | -0.078 | -0.044 |
| Panel B: Unexplained Gap | | |
| Income | 0.040 | 0.013 |
| Age | -0.412 | -0.251 |
| Schooling | -0.419 | -0.456 |
| Kids | 0.018 | 0.049 |
| Gender | -0.009 | -0.002 |
| Homeowner | -0.002 | 0.000 |
| Constant | -0.755 | 0.146 |
| Total | -1.537 | -0.500 |
| N | 10550000 | 1185000 |

Notes: This table plots the results from an Oaxaca-Blinder decomposition of mean differences in PM2.5 exposure between African-Americans and non-Hispanic Whites. Column (1) performs this decomposition for the year 2000, whereas column (2) decomposes differences originating in 2015. Panel A displays the amount by which Black-White differences in the respective covariates explain the gap in mean PM2.5 exposure between groups. Panel B presents the amount by which Black-White differences in the respective coefficient estimates explain the gap in mean PM2.5 exposure between groups. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B5—: Decomposition of Quantile Differences in Pollution Exposure into Components Explained by Differences in Individual Characteristics and due to Differences in "Returns" to Characteristics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Year 2000 | | | Year 2015 | | |
| | 10th Percentile | 50th Percentile | 90th Percentile | 10th Percentile | 50th Percentile | 90th Percentile |
| Predicted difference | -2.360 | -1.607 | -0.861 | -1.081 | -0.434 | -0.130 |
| | | | Panel A: Explained Gap | | | |
| Income | 0.004 | -0.003 | -0.001 | 0.001 | 0.000 | 0.001 |
| Age | -0.015 | -0.008 | -0.002 | -0.003 | -0.002 | -0.002 |
| Schooling | 0.002 | -0.006 | 0.001 | 0.003 | -0.001 | -0.021 |
| Kids | 0.004 | 0.004 | 0.002 | -0.001 | 0.000 | 0.002 |
| Gender | -0.002 | 0.001 | 0.001 | 0.0001 | 0.000 | 0.000 |
| Homeowner | -0.041 | -0.010 | -0.120 | -0.034 | -0.018 | -0.056 |
| Total | -0.049 | -0.023 | -0.119 | -0.034 | -0.019 | -0.077 |
| | | | Panel B: Unexplained Gap | | | |
| Income | 0.240 | -0.057 | 0.011 | 0.016 | -0.008 | 0.046 |
| Age | -0.696 | -0.352 | 0.036 | -0.399 | -0.205 | -0.262 |
| Schooling | 0.316 | -0.147 | -0.981 | -0.114 | -0.263 | -0.696 |
| Kids | 0.045 | -0.004 | 0.013 | 0.040 | 0.034 | 0.059 |
| Gender | -0.018 | -0.007 | -0.002 | -0.007 | -0.002 | 0.001 |
| Homeowner | -0.006 | 0.004 | -0.000 | 0.001 | -0.003 | 0.003 |
| Constant | -2.191 | -1.020 | 0.181 | -0.585 | 0.031 | 0.795 |
| Total | -2.311 | -1.584 | -0.742 | -1.047 | -0.415 | -0.053 |
| N | 10550000 | 10550000 | 10550000 | 1185000 | 1185000 | 1185000 |

Notes: This table plots the results from six RIF decompositions of quantile differences in PM2.5 exposure between African-Americans and non-Hispanic Whites, where quantiles are indicate in the column headings. Columns (1)-(3) perform this decomposition for the year 2000, whereas columns (4)-(6) decompose differences originating in 2015. Panel A displays the amount by which Black-White differences in the respective covariates explain the gap in quantile PM2.5 exposure between groups. Panel B presents the amount by which Black-White differences in the respective coefficient estimates explain the gap in quantile PM2.5 exposure between groups. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B6—: Oaxaca-Blinder Decomposition, Census Tract Characteristics

| | (1) Year 2000 | (2) Year 2015 |
|---|---|---|
| Predicted difference | -1.617 | -0.542 |
| Panel A: Explained Gap | | |
| Income | -0.001 | 0.001 |
| Age | -0.007 | -0.002 |
| Schooling | 0.001 | -0.003 |
| Kids | 0.003 | 0.002 |
| Gender | 0.001 | 0.000 |
| Homeowner | 0.007 | 0.014 |
| Neighborhood/Tract | | |
| Tract Miles of Major Highway | -0.162 | -0.061 |
| Tract Total Facility PM2.5 Emissions | 0.001 | 0.000 |
| Tract Public Assistance Income | -0.025 | -0.006 |
| Tract Years of Schooling | -0.151 | -0.042 |
| Tract % Single Family Residence | 0.336 | 0.014 |
| Tract Teen Pregnancy Rate | 0.002 | -0.007 |
| Tract Home Ownership Rate | -0.355 | -0.111 |
| Total | -0.351 | -0.199 |
| Panel B: Unexplained Gap | | |
| Income | -0.052 | 0.014 |
| Age | -0.266 | -0.199 |
| Schooling | -0.271 | -0.324 |
| Kids | 0.022 | 0.055 |
| Gender | -0.008 | -0.002 |
| Homeowner | -0.001 | -0.005 |
| Neighborhood/Tract | | |
| Tract Miles of Major Highway | -0.144 | -0.034 |
| Tract Total Facility PM2.5 Emissions | 0.001 | -0.020 |
| Tract Public Assistance Income | -0.220 | 0.008 |
| Tract Years of Schooling | -4.033 | -1.051 |
| Tract % Single Family Residence | 4.300 | 0.217 |
| Tract Teen Pregnancy Rate | -0.030 | -0.017 |
| Tract Home Ownership Rate | -1.048 | -0.290 |
| Constant | 0.732 | 1.314 |
| Total | -1.252 | -0.343 |
| N | 10550000 | 1139000 |

Notes: This table plots the results from two Oaxaca-Blinder decompositions of mean differences in PM2.5 exposure between African-Americans and non-Hispanic Whites. Column (1) performs this decomposition for the year 2000, whereas column (2) decomposes differences originating in 2015. Panel A displays the amount by which Black-White differences in the respective covariates explain the gap in mean PM2.5 exposure between groups. Panel B presents the amount by which Black-White differences in the respective coefficient estimates explain the gap in mean PM2.5 exposure between groups. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B7—: Decompositions of PM2.5 Exposure Changes 2000-2015 by Race

| | (1)<br>Non-Hispanic White | (2)<br>African American |
|---|---|---|
| Average PM2.5 Change by Race: 2000-2015 ($\Omega(\phi)$) | -4.706 | -5.728 |
| Decomposition: | | |
| Unweighted Average Tract Change: 2000-2015 ($\bar{\omega}(\phi)$) | -5.176 (110%) | -5.349 (93.3%) |
| Change in Covariance 2000-2015 ($\Gamma^{OP}(\phi)$) | 0.478 (-0.10%) | -0.375 (6.6%) |

Notes: This table decomposes the average 2000-2015 change in pollution exposure by race into that which can be explained by unweighted Census-tract level changes in PM2.5 versus reallocation of population shares to cleaner/dirtier Census tracts over time. Source: Decennial Census, American Community Survey, and Di et al. (2016).

Table B8—: Sensitivity Analysis: The Impact of the 2005 Implementation of PM2.5 Standards on PM2.5 levels

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | | EPA Monitor Data | | Unweighted Regression | | Excluding Neighboring CZ's | |
| | PM2.5 | ln(PM2.5) | PM2.5 | ln(PM2.5) | PM2.5 | ln(PM2.5) | PM2.5 | ln(PM2.5) |
| PM2.5 Nonattain×Post | -0.727 | -0.036 | -0.716 | -0.033 | -0.907 | -0.046 | -0.842 | -0.047 |
| | (0.080) | (0.006) | (0.140) | (0.009) | (0.120) | (0.009) | (0.100) | (0.008) |
| Year FE State-Year FE | X | X | X | X | X | X | X | X |
| County FE | X | X | X | X | X | X | X | X |
| Observations | 32360000 | 32360000 | 9386000 | 9386000 | 32360000 | 32360000 | 16820000 | 16820000 |

Notes: This table presents regression coefficients from 8 separate versions of equation (3), one per column, where the dependent variable consists of PM2.5 or ln(PM2.5) for an individual in a given year. Columns (1) and (2) replicate our main results from Table 3. Columns (3) and (4) explores sensitivity to using EPA monitor data instead of data from Di et al. (2016). EPA monitor data is averaged to the county level and then assigned to individuals based on county of residence. Columns (5) and (6) explore sensitivity to running regressions without Census survey weights. Columns (7) and (8) explore regressions that drop observations from commuting zones that are adjacent to the 2005 PM2.5 nonattainment regions. Source: Decennial Census, American Community Survey, EPA NAAQS Greenbook, EPA AQS Datamart, Di et al. (2016).